Measuring sustainable intensification: Combining composite indicators and efficiency analysis to account for positive externalities in cereal production

Abstract

We combine the use of a stochastic frontier analysis framework and composite indicators for farm provision of environmental goods to obtain a farm level composite indicator reflecting sustainable intensification. The novel sustainable intensification composite indicator that is developed accounts for multidimensional market and non-market outputs, namely the economic performance of cereal farms (i.e. market production value) and the associated positive environmental impacts of production (e.g. positive environmental externalities). The composite indicator integrates three different indicators for the provision of environmental goods into a stochastic frontier analysis: a) agri-environmental payments; b) the ratio of rough grassland and permanent pasture area to total utilised agricultural area; and c) land use diversity, as measured by the Shannon Index. We apply this approach to a panel of data for 106 cereal farms in England and Wales during the period 2010-2012. Results indicate that farm rankings on the indicator vary substantially depending on the weight given to the different environmental aspects/indicators, suggesting that single indicators of the provision of environmental goods may not provide a true reflection of the environmental performance of farms. We illustrate a simple approach that captures the aspects of sustainable intensification of farms in a much more holistic way, i.e. by producing a distribution of sustainable intensification scores for each farm reflecting different weightings of evaluation criteria. To reduce the dimensionality of this distribution farms are classified into four distinct groups according to the shape of this distribution, with some farms found to perform well under all combinations of weights for evaluation criteria, while others always perform poorly. This distribution-based analysis provides a greater depth of information than traditional approaches based on the generation of a single sustainable intensification score.

1. Introduction

A growing awareness of the externalities associated with agricultural production has been a key driver of the development of agricultural policies in the EU for more than 30 years (Potter and Goodwin, 1998). Following decades of policies oriented towards increased productivity in the decades after 1945 (Stoate et al., 2001), without much consideration for the environmental consequences of such an approach, the focus of EU agricultural policy changed from the mid-1980s toward the promotion of a more sustainable agriculture, through provision of incentives to farmers "to work in a sustainable and friendly manner", providing a "better balance between food production and the environment" (European Commission, 2014; Buckwell et al., 2014). Initially, such policies focussed on protection of natural resources, biodiversity and cultural landscapes. In the last 10 years, since the volatility in commodity prices of 2007/8 and growing concerns about food security, attention has moved towards measures aimed at promoting ecosystem services beneficial to production (Plieninger et al., 2012; Tittonell, 2014) and their role in contributing to 'sustainable intensification' (Tilman et al., 2011).

A narrow definition of 'sustainable intensification' (SI) is simply improved resource use efficiency, i.e. 'producing more with less'. However, a more complete understanding has to encompass the positive and negative externalities of agriculture, i.e. the supply of ecosystem services beyond provisioning. However, the interlinkages between agricultural production and these environmental outputs, and the trade-offs between them, are complex, making it extremely difficult to envision what sustainable agriculture (or for this matter sustainable intensification) actually comprises (Pretty, 1997). The difficulty in generating models of sustainable intensification in agriculture is compounded by two factors. First, the spatial heterogeneity of both the environments in which agriculture operates and the production systems employed. Second, sustainable intensification in agriculture is an anthropogenic concept that is also subject to heterogeneity, as individuals and societies value the ecosystem services provided by agriculture differently and have different levels of awareness and understandings of the interlinkages and trade-offs between these ecosystem services. These differences mean that the definition of sustainable intensification in agriculture, as a concept, varies, even amongst international organisations, although some overlap exists. Thus, for example, the Montpellier Panel and Save and Grow report (FAO, 2011) define sustainable intensification as: "producing more outputs with more efficient use of all inputs - on a durable basis - while reducing environmental damage and building resilience, natural capital and the flow of environmental services"; The Royal Society (2009) defines sustainable intensification as "… yields are increased without adverse environmental impact and without the cultivation of more land"; and the UK Foresight Report (Foresight Report, 2011) states, when referring to sustainable intensification, "simultaneously raising yields, increasing the efficiency with which inputs are used and reducing the negative environmental effects of production". While the first and third definitions are similar, the second definition highlights a slight but important difference, i.e. that SI is considered to be achieved by increasing provisioning services while simultaneously not increasing negative environmental externalities. Taking all these definitions into account, and for the purposes of this study, sustainable intensification can be understood as increasing the market-based dimension of sustainability (i.e. agricultural yield) without decreasing the capacity to provide (largely) non-market dimensions, i.e. environmental services. This understanding of SI evokes the more generalised definition offered by Jules Pretty (Pretty, 1997) that SI represents: "increasing food production from existing farmland while minimising pressure on the environment". These different interpretations of SI have generated a debate about the pathways to achieving SI, with various models being put forward, including land sparing, land sharing, and competitive advantage (Franks, 2014).

While there are different interpretations of what constitutes SI, and consequently different proposed pathways to achieving it, all these approaches face the common problem of how to measure success. The questions arising from this are: (a) what dimensions of SI need to be measured; (b) what metrics are appropriate to capture these dimensions; and (c) how can these metrics be combined into a composite measure of SI that truly reflects the relative importance of each dimension, i.e. under what weighting system?

It seems clear from the definitions above that any meaningful SI measure/metric needs to take into account both provisioning outputs and the environmental impacts of land management, i.e. the inclusion of environmental externalities into technical efficiency analysis. Traditionally, metrics of the environmental dimension have focussed solely on the negative externalities associated with agricultural production. However, there can also be 'positive' environmental outputs associated with productive land management, for example the provision, or improvement, of semi-natural habitats and the positive effects on wildlife and biodiversity that result (Mattison and Norris, 2005; OECD, 1999). Therefore, measuring SI is not the same as measuring sustainability, as the SI measure excludes some key dimensions of sustainability, such as social impacts. In part, this results from limitations on the information available to produce SI, such as, for example, the Defra Farm Business Survey (FBS) data, as used in this study.

Approaches to incorporating environmental externalities into technical efficiency analysis began with Färe et al. (1989). While the focus of this early work was solely directed towards the negative externalities associated with agricultural production (Färe et al., 1989, 1996, 2001; Lansink and Reinhard, 2004; Murty et al., 2006; Reinhard and Thijssen, 2000; Reinhard et al., 1999, 2002) more recent technical efficiency analysis has also incorporated the provision of positive externalities (Omer et al., 2007; Areal et. al., 2012; Sipiläinen and Huhtala, 2013; van Rensburg and Mulugeta, 2016). More recently, work by Ang et al. (2015) analysed the impact of dynamic profit maximisation on biodiversity, for a sample of UK cereal farms, using a DEA approach.

The limitation of some of the approaches adopted to date, i.e. that use composite indicators to account for different dimensions of SI, is that these composite indicators can only reflect fixed and usually pre-determined relative weightings of these dimensions. Some other approaches to developing composite indicators of SI have not relied on pre-determined weights, but have used statistical procedures such as DEA and factor analysis to determine them. For instance, Barnes and Thomson (2014) used a form of factor analysis to provide weights to individual indicators to form composite indicators of SI. However, the weights for SI indicators obtained in all these previous studies are presented as a single set of numbers, based on the averages of the weight distribution, while variation of these weights is not explored. This may give these composite indicators a form of starting point bias and makes them of limited value to policy makers, who would view the choice of weights for these dimensions as a fully anthropogenic decision. This paper explores the potential for the use in composite SI indicators of a number of different indicators of environmental outputs under multiple weightings, on the basis that all of these alternatives capture some valid aspect of environmental goods at the farm level. To explore the feasibility of constructing such an indicator this study uses a stochastic frontier framework to undertake technical efficiency analysis at the farm level to test a mechanism to create a composite indicator of sustainable intensification combining provisioning outputs with indicators representing multiple dimensions of environmental goods provision.

Since we face farms with multiple outputs (e.g. market and non-market/environmental outputs) we estimate farm level efficiency through the use of an output distance function (Coelli et al., 2005), where the farm production frontier directly accounts for both market and non-market goods.

To overcome the problem of there being no single correct weighting of the relative importance of the different dimensions of environmental output, we explore a method to capture all potential integer weighting combinations within and between the multiple SI indicator. We therefore estimate 66 efficiency stochastic frontier models that account for different combinations of weights for the dimensions of environmental goods provision, to create a single composite indicator for SI. This approach provides a much more nuanced picture (i.e. a probability distribution) of SI at the farm level, than would relying on the use of a single snap-shot, based on a single set of weights.

Methods

1.1. Data

The analysis reported here uses data in the form of a balanced panel of 106 specialist cereals farms drawn from the annual Defra Farm Business Survey (FBS) for England and Wales, between 2010 and 2012[1]. Data were drawn solely for the 'specialist cereals' farm type, to minimize the level of heterogeneity due to differences in farming system. While the FBS provides financial data on each farm business, alongside crop, livestock and land use data, it has been historically more limited with respect to environmental metrics (e.g. metres of hedges or pond areas) and physical measures of inputs (e.g. kilograms of nitrogen fertiliser). This has led to the analysis herein drawing on a more limited range of data, and using environmental payments as a composite metric for some environmental outputs, i.e. where these payments can reasonably be assumed to capture public benefit from environmental activities. While drawing on such proxy metrics limits, in part, the results generated, these data are sufficient to demonstrate an approach for quantifying SI that can be further refined in the future through the use of better data. To illustrate, the most recent FBS year (2016/17) captures, for the first time, the areas of certain landscape features, including buffer strips, hedges and catch/green cover/nitrogen fixing crops.

[1] We selected all Specialist Cereals farms that were in the FBS within the period of the study that had all information required for the model (i.e. 106 farms).

Farm provisioning outputs were captured using two separate metrics: a) cereals enterprise output (£)[2]; and b) other agricultural outputs, i.e. other crops and livestock (£)[3]. Farm environmental outputs were captured by the three metrics described below. To capture inputs, the following metrics were included: utilised agricultural area (ha); labour use (hours per annum); machinery costs (£); other costs, including crop protection and animal costs (£). Also employed, as explanatory variables in the modelling, were a set of socio-economic variables, such as farmer age and education level, financial pressure (debt/asset ratio) and membership of certification and assurance schemes. Farmer age has been included as a covariate as this may be related to SI, with younger farmers being more concerned about sustainability. We also hypothesise that more educated farmers may have more knowledge of the approaches required to increase production in a sustainable way. We hypothesise that farmers under financial pressure may de-emphasise sustainability goals in favour of output, or profit-based, business goals, and so achieve lower SI scores than farmers not under financial pressure. Additionally, these three factors, have been previously identified as determinants of technical efficiency (Hadley, 2006; Wilson et al., 2001). Finally, assurance scheme membership has been included as such schemes often include sustainability requirements, and so we hypothesise that farmers with assurance schemes have higher SI scores. This last factor has, to our knowledge, has not been examined as a potential driver of SI or efficiency in previous studies.

The FBS contains information on the geographical location of the farm as associated with the landscape type (‘National Character Area’) [4] in which the farm lies. This information has been used to identify and map any spatial influences on SI.

Summary descriptive statistics for the sample of farms, based on the variables used in the analysis, can be found in Table 1.

[2] The FBS dataset reflects input use by farms primarily in value terms. For consistency sake, therefore, both outputs and inputs are denominated in value terms. However, for the purpose of this analysis these deflated data can be assumed to act as proxies for measures of volume. Data has been deflated using the agricultural price indices for inputs and outputs and the CPI for the environmental payments.
[3] Although our data is obtained for specialised cereal farms, some of these farms will have livestock, although this will be a minority enterprise.
[4] National Character Areas are landscape units defined by geology, topography, soil type, land cover, history, and cultural and economic activity. Their boundaries follow natural linear features in the landscape rather than administrative boundaries.

Variable	Mean	Std. Dev
Cereals (£)	237,417	274,964
Other output (£)	30,215	42,124
EI (Agri-env payments) (£)	15,737	22,790
EI (Permanent grassland) (proportion of UAA)	0.157	0.147
EI (Land use diversity) (Index)	0.598	0.134
UAA (ha)	333	313
Labour (number of hours per annum)	47,220	58,156
Machinery (£)	131,311	125,514
Crop and animal cost (£)	122,242	136,991

Table 1. Descriptive statistics for sample farms (average 2010-2012). Key: EI = Environmental Indicator, UAA = Utilised Agricultural Area.

1.2.Measurement of efficiency

Buckwell et al. (2014) explored the use of such multi-dimensional composite indicators within the framework of economic theory, and suggested that provisioning and environmental dimensions can be seen as two dimensions of a production possibilities frontier (PPF), where the PPF serves to 'depict the challenge of sustainable intensification'. We accept this principle in our analysis and incorporate composite indicators for the provision of environmental goods as another dimension to the standard technical efficiency analysis.

We use an output distance function approach to describe technology in a way that allows efficiency to be measured for multi-input, multi-output farms (Coelli et al., 2005). More specifically, we describe the degree to which a farm can expand its outputs given its input vector.

$$P(x) = \{y \in \ R_+^M : x\ can\ produce\ y\} = \{y : (x, y) \in T\} \quad (1)$$

Where y refers to all $M = 3$ market-based, plus environmental outputs of the farm, where environmental outputs are represented by either a single or composite indicator for the provision of environmental goods; x represents all K inputs used in the farm; and T represents the technological set. The distance function is defined on the output set $P(x)$ as

$$D_O(x, y) = \min\left\{\theta : \left(\frac{y}{\theta}\right) \in P(x)\right\}\ for\ all\ x \in R_+^K \quad (2)$$

We posit that a translog function for the parametric distance function with M outputs and K inputs offers some attractive properties, such as flexibility and allowing the imposition of homogeneity, which makes it the preferred form in the literature (Lovell et al., 1994; Coelli and Perelman, 1999; Brümmer et al., 2002, 2006; Areal et al., 2012).

$$\ln D_{Oi} = \alpha_0 + \sum_{m=1}^{M} \alpha_m \ln y_{mi} + \frac{1}{2}\sum_{m=1}^{M}\sum_{n=1}^{M} \alpha_{mn} \ln y_{mi} \ln y_{ni} + \sum_{k=1}^{K} \beta_k \ln x_{ki} +$$

$$+\frac{1}{2}\sum_{k=1}^{K}\sum_{l=1}^{K} \beta_{kl} \ln x_{ki} \ln x_{li} + \sum_{k=1}^{K}\sum_{m=1}^{M} \delta_{km} \ln x_{ki} \ln y_{mi} \; ; i = 1, \dots, n \qquad (3)$$

where i denotes the ith farm in the sample. Using linear homogeneity of the output distance function in outputs, equation (3) can be transformed into an estimable regression model by normalising the function by one of the outputs[5] (Lovell et al, 1994). From Euler's theorem, homogeneity of degree one in output implies

$$\sum_{m=1}^{M} \alpha_m + \sum_{m=1}^{M}\sum_{n=1}^{M} \alpha_{mn} \ln y_{ni} + \sum_{m=1}^{M}\sum_{k=1}^{K} \delta_{km} \ln x_{ki} = 1 \qquad (4)$$

which will be satisfied if $\sum_{m=1}^{M} \alpha_m = 1$, $\sum_{m=1}^{M} \alpha_{mn} = 0$ for all n, and $\sum_{m=1}^{M} \delta_{km} = 0$ for all k, which is equivalent to normalising by one of the outputs leading to

$$\ln D_O\left(\frac{y_i}{y_{2i}}, x\right) = \ln D_O \frac{1}{y_{2i}}(y_i, x) \qquad (5)$$

and

$$-\ln y_2 = \alpha_0 + \sum_{m=1}^{M-1} \alpha_m \ln \frac{y_{mi}}{y_{2i}} + \frac{1}{2}\sum_{m=1}^{M-1}\sum_{n=1}^{M-1} \alpha_{mn} \ln \frac{y_{mi}}{y_{2i}} \ln \frac{y_{ni}}{y_{2i}} + \sum_{k=1}^{K} \beta_k \ln x_{ki} +$$

$$+\frac{1}{2}\sum_{k=1}^{K}\sum_{l=1}^{K} \beta_{kl} \ln x_{ki} \ln x_{li} + \sum_{k=1}^{K}\sum_{m=1}^{M-1} \delta_{km} \ln x_{ki} \ln \frac{y_{mi}}{y_{2i}} + \varepsilon_i - z_i \qquad (6)$$

where ε_i is a symmetric random error term that accounts for statistical noise and z_i is a non-negative random variable associated with technical inefficiency.

2.3 Indicators of the provision of environmental goods

We make use of three indicators of the provision of environmental goods, with these being commonly employed in the literature: agri-environmental payments (Hasund, 2013); the area of rough grazing and permanent pasture as a proportion of the total utilised

[5] We normalised the function using the cereals value.

agricultural area (Barnes et al. 2011; Areal et al., 2012; Barnes and Thomson, 2014) and the widely used Shannon Index for land use diversity (LUD) (Westbury et al., 2011).

$$LUD = -\sum_{c=1}^{C} a_c \times \ln(a_c)\,, LUD \geq 0 \qquad (7)$$

where a_c is the proportion of the area occupied by crop c and C is the total number of crops. The Shannon index provides a metric of the number of land use classes on the farm and their proportional representation. A high index value therefore indicates higher crop diversity.

Although the data employed in this study is restricted to agricultural land uses and does not capture total diversity of land cover on the farm, i.e. non-agricultural areas, there is growing evidence that biodiversity is positively affected by heterogeneity in agricultural crop types (Siriwardena et al. 2000; Benton et al. 2003). Indeed, it is for this reason that a crop diversity requirement has been incorporated into the cross-compliance measures of the 2015 CAP.

All the above three measures for the provision of environmental goods are relevant from a policy viewpoint. For example, the latter two are reflected in the EU Common Agricultural Policy (CAP), which makes receipt of direct payments contingent on a minimum level of crop diversity and maintenance of the permanent grassland area. Agri-environmental payments under Pillar II of the CAP are taken to reflect the positive value attributed by society to the local provision of environmental goods through modification of land management practices. These goods include protection of soil and water resources, conservation of farmland biodiversity, protection of historic features and cultural landscapes and the provision of opportunities for recreation and amenity. The indicator capturing the ratio of permanent pasture plus rough grazing area[6] to total utilized agricultural area allows for the identification of farms undertaking low-intensity management, which enhances the provision of areas of high nature value semi-natural habitats. These areas provide a number of environmental benefits such as soil structure improvement, renewal of ground water and flooding control through enhanced infiltration, reductions in water runoff and higher soil organic carbon density (Altieri, 1999: Menta et al., 2011; Leifeld et al., 2005). Indicators based on the presence of

[6] Permanent area refers to land used permanently, for 5 years or more, for herbaceous forage crops, either cultivated or growing wild (European Council, 2003) whereas rough grassland is non-intensive grazing grassland.

permanent grassland have been previously used in SI related studies by Areal et al. (2012) and Barnes and Thomson (2014).

Undoubtedly, the three environmental indicators used here reflect the provision of a wide range of environmental outputs associated with the management of agricultural land, with each indicator capturing a different dimension of environmental provision, although there is some overlap between them.

2.4. Sustainable intensification indicators

As discussed above, a number of indicators have been used in the literature to capture the provision of environmental goods at the farm level. In this study we explore the extent to which the use of different indicators of the provision of environmental goods leads to different SI outcomes. To achieve this, we carry out a stochastic frontier analysis (SFA) using each of these environmental indicators in separate models to estimate farm level efficiency, see models M1-M4 shown in Table 2. The farm efficiency estimates obtained from models M2-M4 we equate with three different indicators of SI, with each of these indicators reflecting the provision of different environmental goods (i.e. different components of the totality of farm provision of environmental goods). The use of 'efficiency' measures as an indicator of 'sustainable intensification' follows the work of Gadanakis et al. (2015), who used DEA to create a composite SI. Hence, we equate the farm efficiency scores obtained from efficiency measures when augmented with provision of environmental goods with what could be called eco-efficiency measures. Eco-efficiency and SI indicators are therefore assumed to be synonymous, i.e. eco-efficiency and SI are closely related concepts, where both are based on the same principle of generating more output while using fewer resources and generating fewer environmental externalities. The OECD defined eco-efficiency as: "Eco-efficiency is reached by the delivery of competitively-priced goods and services that satisfy human needs and bring quality of life, while progressively reducing ecological impacts and resource intensity throughout the life cycle, to a level at least in line with the earth's estimated carrying capacity" OECD (1998). This is similar to the definitions of SI. Eco – efficiency brings together environmental and economic goals contributing towards sustainable development (OECD, 1998). The eco-efficiency literature also makes use of holistic indicators. Indicators for eco-efficiency began by using ratios that relate the economic value of goods and services produced to the environmental impacts or pressures associated with the production process. These made use of simple, solitary indicators such as GDP/emissions of pollutants, or units of output per unit of environmental impact or pressure (Picazo-Tadeo et al., 2012). However, this type of ratio-based indicator was not suitable for the incorporation into the same indicator of a number of different outputs (economic output) and inputs (environmental impact). As a consequence of this limitation, new indicators were developed where a set of inputs and outputs were aggregated using weights, the values for which were typically assigned by a panel of experts, or individual assessment (i.e. no mathematical/statistical methods were used). Our approach integrates environmental indicators into efficiency analysis in a different way (i.e. incorporating a set of composite indicators for the provision of environmental goods into stochastic frontier analysis obtaining farm level distributions of SI rather than single 'snap shot' composite indicator.

The comparison of SI indicators obtained from the models M1-M4 sheds light on both the quantity and the type of provisioning and environmental goods being provided by farms.

Model		**Description**
M1		Baseline technical efficiency model not accounting for environmental externalities
M2		Technical efficiency plus provision of environmental goods using agri-environmental payments as indicator
M3	SI Indicators	Technical efficiency plus the ratio of rough and permanent pasture area to total utilized agricultural area as an indicator of provision of environmental goods
M4		Technical efficiency plus LUD as an indicator of provision of environmental goods

Table 2. Description of the models

2.5. Composite indicators

When combining indicators into composites, the weights given to each indicator have a significant bearing on the interpretation of that composite indicator (Barnes and Thomson, 2014; OECD, 2008). Consequently, the allocation of weights needs to be well informed to ensure that the composite indicator captures the 'true' or 'optimal' relative importance of these dimensions of the environment, i.e. as reflected in human values. However, there is often no way to judge the relative importance of different environmental indicators, either because appropriate weights have never been systematically generated, or because consensus on the relative importance of environment dimensions cannot be reached (Mauchline et al., 2012). The default response in these circumstances is to assume that each indicator represents a different but equally valid dimension of environmental goods provision, regardless of whether this is actually the case. As a means to circumventing this uncertainty, we apply a methodology developed by Areal and Riesgo (2015), which obviates the need to manually, or statistically, allocate weights to the components of aggregate indicators. This methodology is based on the assumption that the use of a set of composite indicators using every possible weighting combination accounts for both the range of possibilities that farmers have available to provide environmental outputs and the range of values that society puts on those environmental outputs. The validity of this approach is based on the further assumption that sustainable agriculture is not achieved by delivering a combination of outputs in fixed proportion, but rather can be achieved by a distribution across different combinations of outputs.

We obtain only a partial picture of SI (i.e. the efficiency level once the provision of environmental output is taken into consideration in the production function) from models M2, M3, and M4, since each of these indicators only account for the provision of a fraction of the environmental output generated by each farm (i.e. SI status will differ depending on which indicator is used). We therefore build a 106×3 matrix EG using the 3 indicators for the provision of environmental goods. Each indicator is normalised using the distance method $\left(EG_i = \frac{eg_i}{max(eg)}\right)$, which measures the relative position of an indicator to a reference point, in this case the maximum value of the indicator in the sample. This allows us to rescale each indicator to a dimensionless scale $(0, 1]$.

We weight and aggregate[7] the individual indicator matrix EG as follows:

$$CEG = EG \times W' \quad (8)$$

where the weighting matrix W is generated with the following features: each element of the matrix can take values $\{0,0.1,0.2, \dots ,1\}$, and the rows of the weighting matrix are a combination of elements (weights) where the sum of elements in each row equals 1. The total number of combinations holding these rules is 66, meaning that W is a 66×3 weighting matrix. We then obtain CEG, a 106×66 matrix. Finally, we estimate the model from equation (6) using the matrix CEG of 66 composite indicators for the provision of environmental values to create a composite indicator of SI, i.e. the Composite Sustainable Intensification (CSI) indicator. Hence, we run 66 models using each of the weighting combinations to obtain 66 *CSI* per farm. Farms are then ranked, relative to other farms, according to how well they score in each of the 66 *CSI*. This information is summarised in a farm rank distribution representing individual farm SI performance. As an illustration of the possibilities of using this information for policy purposes, farms are grouped into four distinct classes according to their performance on all 66 indicators.

2.6. The Stochastic Frontier Analysis (SFA)

We use a Bayesian Markov Chain Monte Carlo (MCMC) procedure (see Koop, 2003 for a detailed explanation) for the model estimation. One advantage of the MCMC approach is that the distribution of the individual farm inefficiencies is automatically mapped as part of the estimation process, rather than having to be estimated ex-post as in the classical approach. The standard stochastic output distance function model, and the extended model to account for the provision of environmental outputs, can be specified as equations 9 and 10 (below) respectively.

$$y_{it} = x_{it}\beta + \varepsilon_{it} - z_i \quad (9)$$

$$y_{it} = x_{it}\beta + ei_{it}\psi + \varepsilon_{it} - z_i \quad (10)$$

with the inefficiency term being common for both approaches

$$z \sim G(K\phi, \omega) \quad (11)$$

[7] Equation (8) implies that we use the additive aggregation rule for the sustainable intensification composite indicator.

where y_{it} is a vector of N observations of the logarithm of cereal production for farm i in year t; x_{it} is an $N \times m$ matrix of the logarithm of other outputs (excluding environmental externalities) and inputs and interlinkages between them, given a translog function for farm i in year t; ei_{it} is a matrix for the environmental indicator (i.e. provision of environmental goods indicator) and its interlinkages with other outputs and inputs for farm i in year t; ψ is the coefficient associated with the environmental indicator; ε and z are vectors that account for a normally distributed error and farm inefficiency respectively.

The farm inefficiency term z follows a gamma distribution with parameters α and farm mean efficiency $(K\omega)$; K is a $T \times r$ matrix of explanatory variables for inefficiency and ω is an $r \times 1$ vector of parameters associated with the explanatory variables for inefficiency.

3 Results

The Bayesian Markov Chain Monte Carlo (MCMC) procedure generated 30,000 random draws from the conditional distributions with, 5,000 draws discarded and 25,000 draws retained. These 25,000 draws can be considered as a sample from the joint posterior density function of the parameters. Table 3 shows the coefficient estimates obtained from the four models shown in Table 2.

As Table 3 shows, all models produced similar results for the coefficients associated with production inputs. Thus, all coefficient signs are as expected. The UAA and crop and animal costs were the two most important inputs in terms of cereal production, excepting for M4 (land use diversity) where UAA and labour are the two most important inputs. A percentage increase in these inputs leads to relatively high increases in the outputs compared to other inputs such as labour, for example. Very much as expected, the production of other outputs on the farm and rising values on the environmental indicator(s) (i.e. a greater area of the two land-based EI measures and less land cover specialisation) reduced the production of cereals, holding everything else constant, i.e. there is a trade-off between market output (i.e. cereals) and the provision of environmental goods, regardless of the type of environmental good. This is possibly due to a redistribution of resources, especially of land, away from cereals production to other uses, as is the case for model M3, where an increase in the proportion of UAA given over to rough and permanent grassland reduces the area allocated to cereal production. The results in Table 3 suggest that the environmental output draws land away from cereals production, as land use diversity captures increasing complexity, i.e. reducing reliance on one, or a few cereals crops.

Table 3 also shows the role of a number of potential explanatory variables in driving SI. Past research into the impact of farmer age on efficiency has produced mixed results (Wilson et al, 2001; Iraizoz et al., 2006). Replicating the findings of Tan et al. (2010) this analysis finds a clear positive relationship between both age and level of education with level of efficiency, irrespective of the model used. Conversely, Hadley (2006) found a small but significant negative relationship between age and efficiency for cereal farms in England and Wales.

	M1 – Baseline (Non-env.)			M2 - AEP			M3- Grass			M4 - LUD		
	Coeff.	95% posterior coverage regions		Coeff.	95% posterior coverage regions		Coeff.	95% posterior coverage regions		Coeff.	95% posterior coverage regions	
Constant	0.112	0.080	0.143	0.059	0.035	0.092	0.064	0.036	0.098	0.090	0.058	0.100
Other outputs	-0.295	-0.351	-0.244	-0.214	-0.271	-0.161	-0.189	-0.251	-0.126	-0.102	-0.124	-0.060
EO (environmental output)				-0.193	-0.255	-0.128	-0.122	-0.163	-0.083	-0.667	-0.651	-0.506
UAA	0.597	0.441	0.757	0.731	0.600	0.652	0.587	0.444	0.765	0.257	0.218	0.394
Labour	0.063	0.003	0.142	0.050	0.002	0.127	0.044	0.002	0.114	0.024	-0.036	0.079
Machinery and general costs	0.014	3.E-04	0.051	0.010	4.E-04	0.039	0.011	5.E-04	0.039	0.007	-0.056	0.099
Crop and animal costs	0.214	0.095	0.328	0.105	0.026	0.192	0.169	0.049	0.300	0.014	-0.017	0.112
Constant	0.494	0.371	0.678	0.446	0.336	0.607	0.472	0.356	0.648	0.435	0.328	0.594
Farmer's age	-1.287	-1.705	-0.871	-1.233	-1.646	-0.817	-1.301	-1.725	-0.881	-1.268	-1.667	-0.868
Education	-0.849	-0.391	0.091	-0.546	-0.994	-0.072	-0.755	-1.233	-0.255	-0.641	-1.079	-0.180
Finance pressure	-1.118	-0.553	0.028	-0.583	-1.133	0.001	-0.352	-0.902	0.238	-0.716	-1.220	-0.167
Assurance Scheme	-0.253	0.642	1.742	0.631	-0.312	1.760	0.001	-0.963	1.163	0.567	-0.335	1.681

Table 3. Slope parameters for Models M1-M4

The average technical efficiency (TE) of the sample for the model that does not account for environmental outputs (M1) is 0.88 whereas for models M2, M3, and M4, efficiency (i.e. SI) is 0.90, 0.90 and 0.91 respectively. Sample medians are 0.90, 0.92, 0.91 and 0.92 respectively. Figure 1 shows the kernel distributions of the posterior means of farm technical efficiency evaluated over models M1- M4. The results suggest that including environmental goods in total farm outputs shifts the efficiency distribution toward the right (i.e. the aggregate SI score of farms is, on average, higher with the addition of non-market outputs). This suggests that farmers are as efficient at producing environmental outputs as they are provisioning outputs, if not more efficient. However, it is worth noting that improving SI requires more than increasing the area of permanent pasture, land in stewardship or a greater diversity of crops diversification. In a wider sense, SI should also capture the farmer's use of the crop(s), and extending the analysis through the inclusion of this information into the model would improve the SI measure.

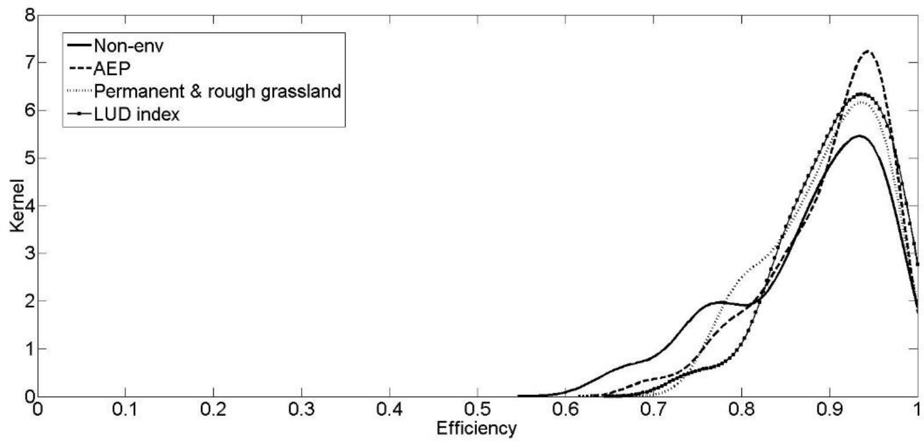


Figure 1. Kernel distributions of the posterior means of technical efficiency across all farms for M1, M2, M3 and M4.

As noted by Areal et al. (2012), when generating SI scores using different model specifications it is worth investigating their differential impacts on individual farm SI rankings. Figure 2 shows that farm efficiency rankings (i.e. farm SI rankings) vary across the four models. These figures allow us to see the extent to which the addition of the different environmental outputs changes the farm efficiency score. As is apparent, the addition of the agri-environment indicator has least impact on farm efficiency score, i.e. the data points are fairly tightly clustered along the no-change line. Conversely, models M3 and M4, i.e. using the ratio of rough and permanent pasture area to total agricultural area and the LUD indicator respectively, produce the most widely distributed data points, indicating significant changes in farm efficiency score.

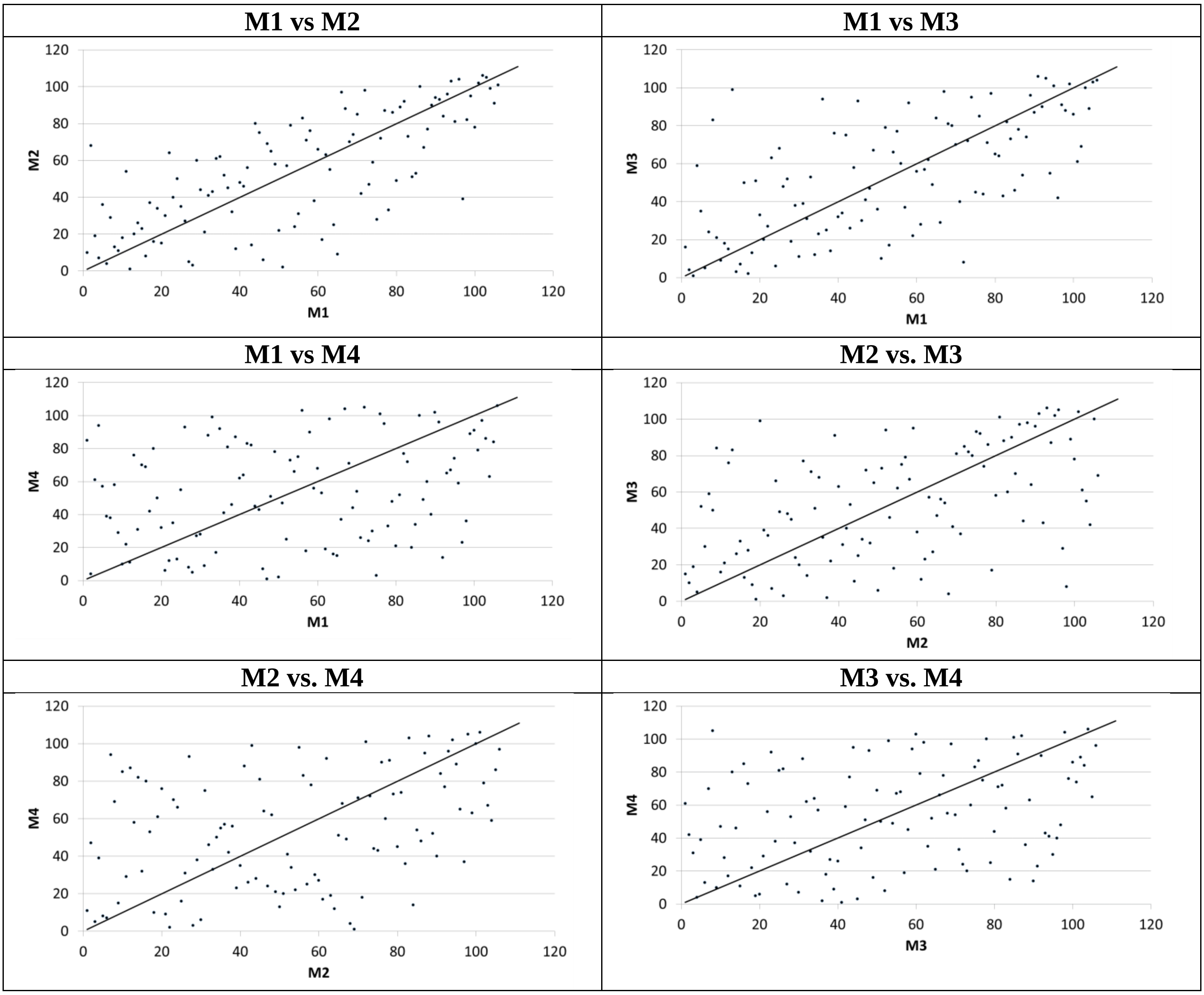


Figure 2. Scatter plots of rankings of efficiency scores

Figure 2 shows that farm SI scores vary markedly on the basis of the environmental indicator chosen. Farm SI scores also vary according to the type of landscape in which the farm is located. To explore this issue further, we analysed changes in SI and SI rankings after grouping farms according to landscape type, following the Swanwick typology of the 159 National Character Areas in England (Swanwick et al., 2007)[8]. Figure 3 shows that when using the LUD indicator, SI scores are higher for farms in upland fringe dairy and stock rearing landscape types than they are in other landscape types. However, this same region is the least efficient when the other environmental indicators are considered. Eastern arable landscapes are consistently efficient, except when weighting heavily for LUD, as there is greater specialisation of farming systems here and simpler crop rotations with more focus on cereals.

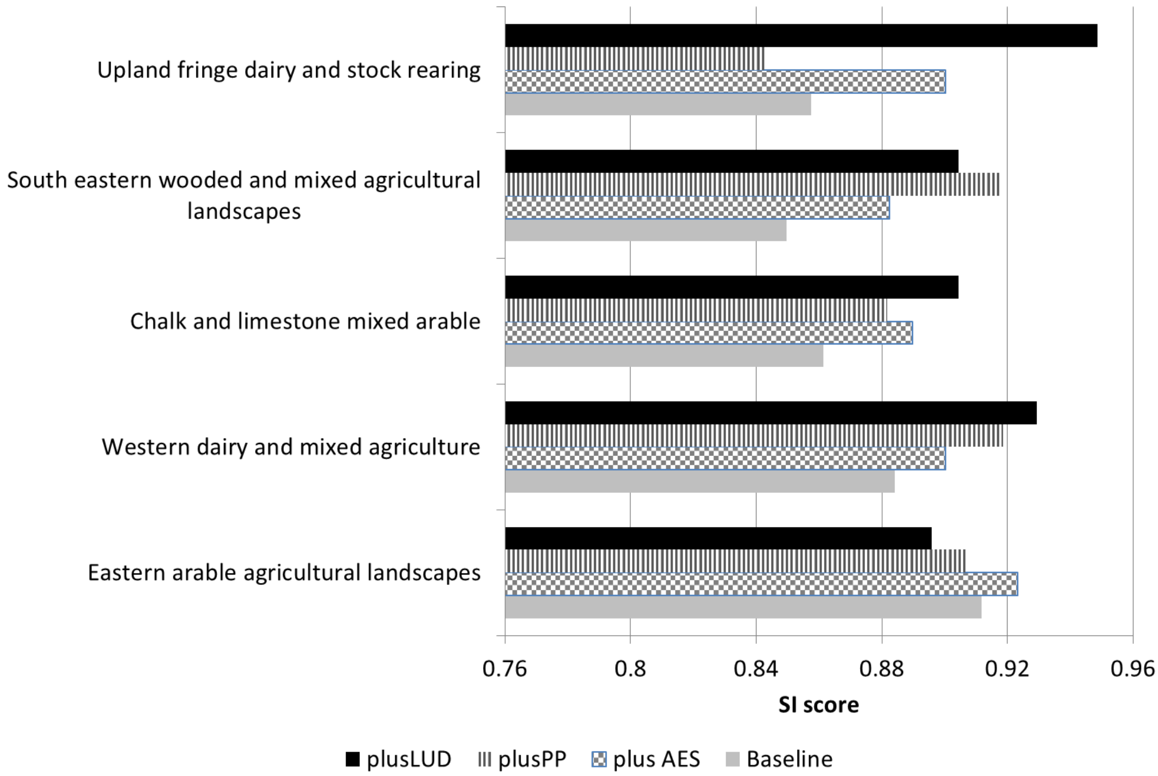


Figure 3. SI scores by model and landscape type

Figure 4 shows how farms change in average efficiency within each landscape type when different environmental indicators are added to farm outputs. The figure shows that farms in the intensive arable eastern claylands significantly drop in SI rank, and those in the upland fringes increase in SI rank, when using LUD as the indicator of provision of environmental goods (M4). When the permanent and rough grassland indicator is added (M3) farms in south eastern wooded and mixed agricultural

[8] Note that the FBS farm classification (i.e. cereal farms) is different from the landscape type classification.

landscapes tend to increase in SI ranking, whereas farms in the upland fringes decrease in SI rank. These findings present compelling evidence that the use of different indicators for the provision of environmental goods may lead to different SI rankings at the farm level, and that the extent of this variation depends to some extent on landscape type.

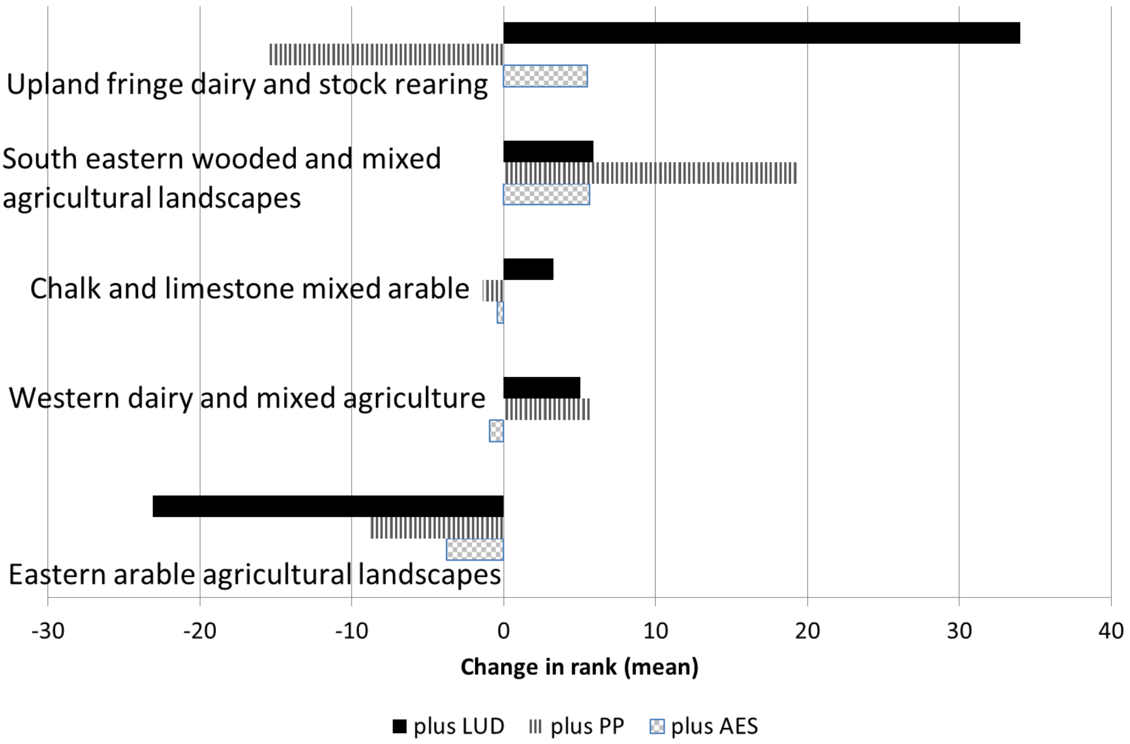
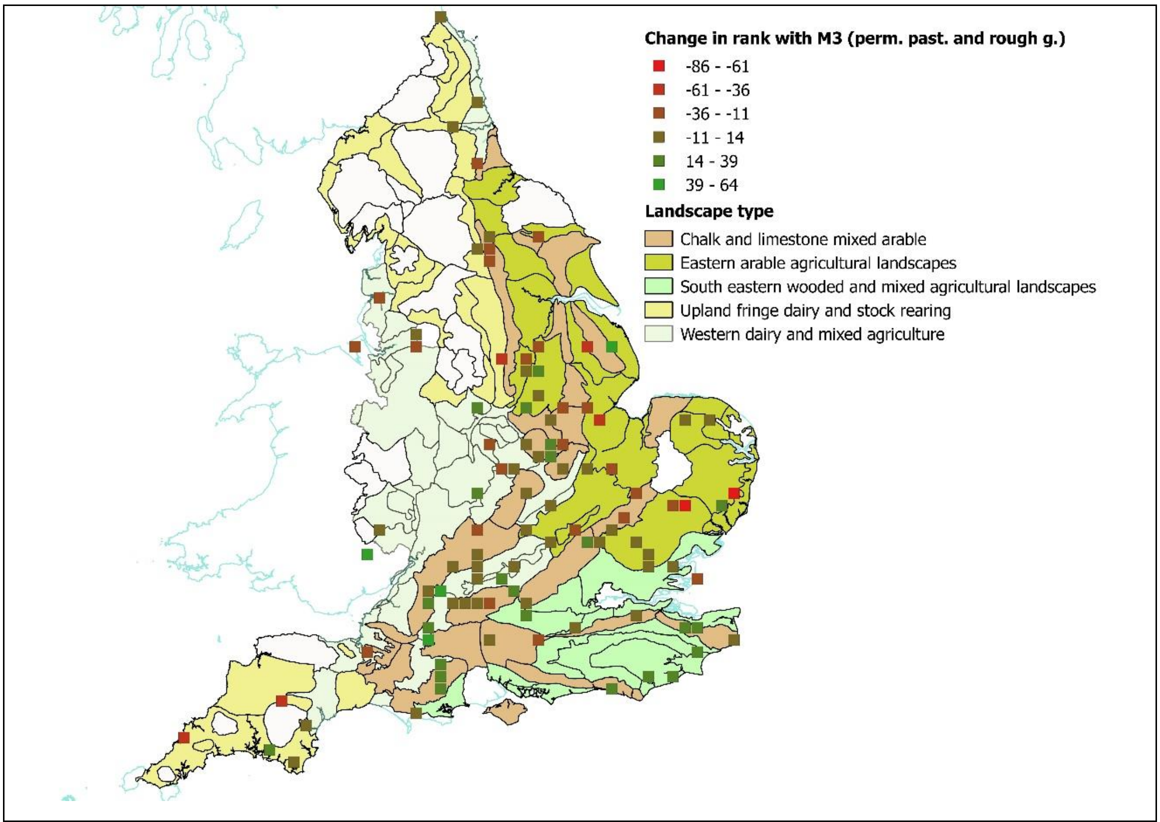


Figure 4. Changes in SI rank resulting from the inclusion of environmental outputs, compared to the baseline model (M1) by landscape type

Figure 5 shows the extent of changes in SI ranking, when provision of environmental goods (permanent grassland and LUD) is accounted for, in interaction with landscape type

5a: Permanent pasture and rough grazing (M3)



5b: Land use diversity (M4)

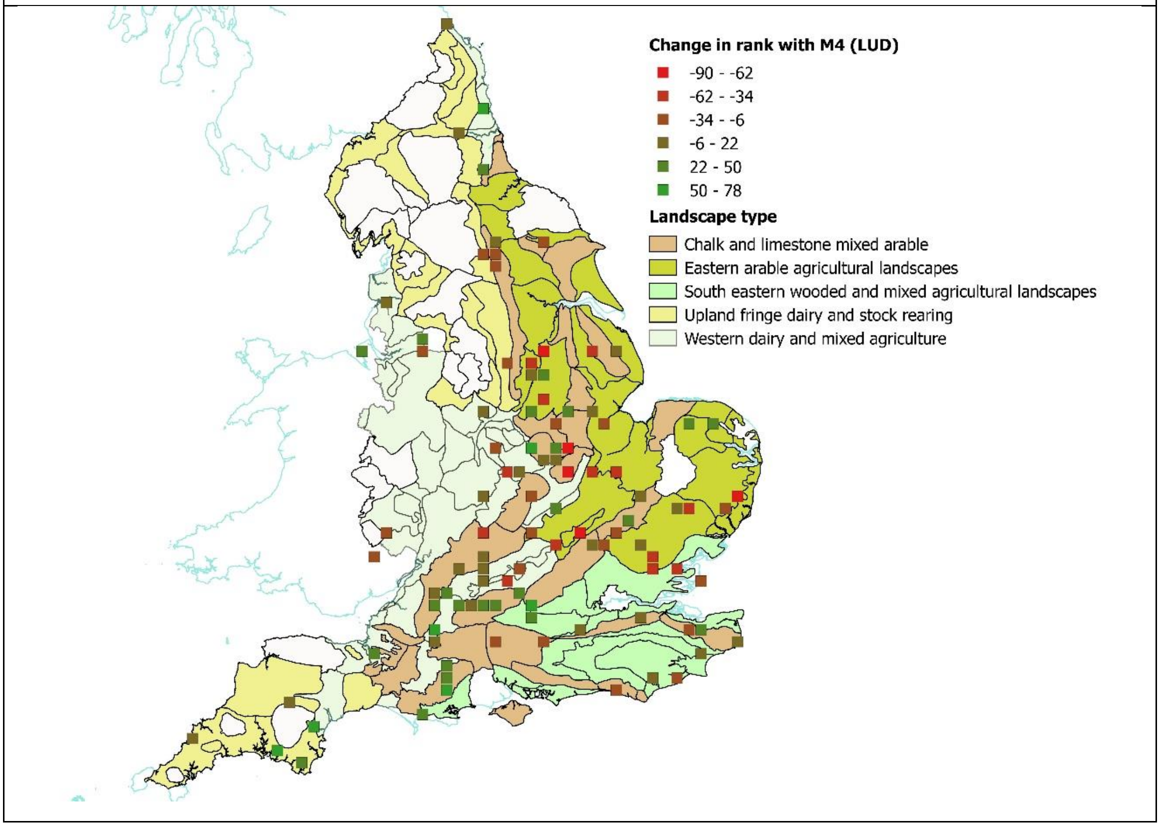


Figure 5. Spatial distribution of the extent of changes in SI ranking when provision of environmental goods (permanent grassland and LUD) is accounted for[9] in interaction with landscape type.

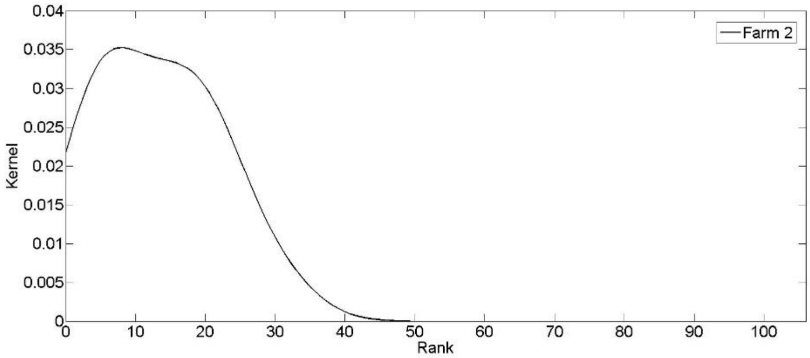
Farms were found to exhibit different patterns in SI scores under different indicator weightings. Figure 6 shows the kernel distributions of rankings for 6 individual farms under the 66 SI indicators. These six farms have been selected to be representative of different farm classes, where the classification is based on the way in which their efficiency changes through the addition to farm outputs, under different environmental indicator weights. As can be seen from the figures, some farms receive very high ranks, for example farms 2 and 38, regardless of how their environmental indicators are ranked. The radar diagrams show why this occurs. Both farms 2 and 38 score well on provisioning outputs, while at the same time scoring either well, or moderately well, on all three environmental indicators.

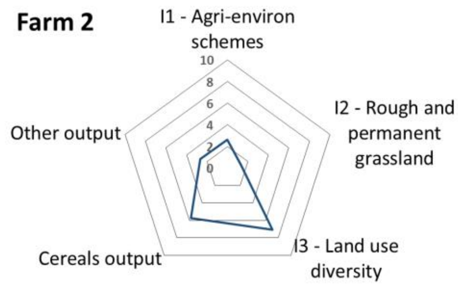
Some farms, i.e. farms 5 and 7, have much more heterogeneity of ranks, leading to broader kernel distributions. This suggests that under some weighting conditions, i.e. for some environmental outputs, they score highly, but in other cases they score poorly. The radar diagram for farm 5 shows that again, provisioning outputs are relatively high, and output on one of the environmental indicators is good, but there is very little output, or no output at all, on the other two environment indicators. When these absent environmental outputs are heavily weighted, therefore, the farm's SI rank suffers.

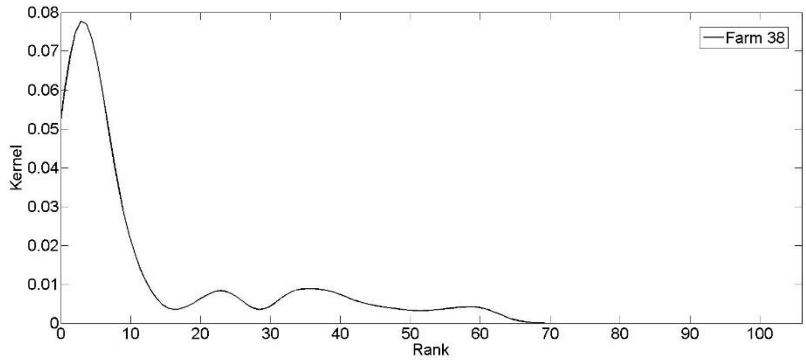
Farms 51 and 100 illustrate the final class of farms, where SI rank score is poor regardless of the way in which the environmental indicators are weighted. In both these cases environmental outputs are low, but not non-existent. However, in this class of farms, even if performance on one environmental indicator is reasonable, the SI rank remains low due to the very low rate of provisioning output per hectare.

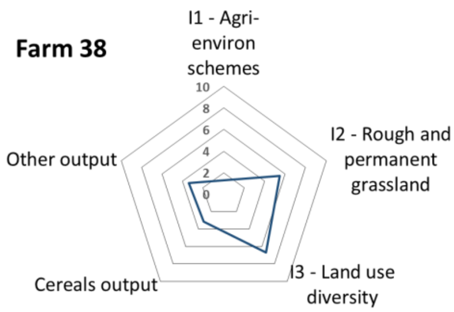
Another interesting outcome is that most farms do well in the case of at least one of the environmental indicators, i.e. there is evidence of some sort of provision of environmental goods on most farms.

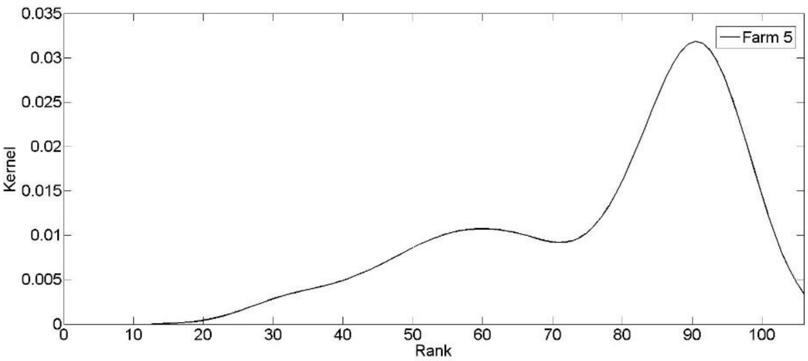
[9] The location of the farms are only approximate random locations within the county in which the farm is located. Location of the farms has only been constrained to the farm's landscape type.

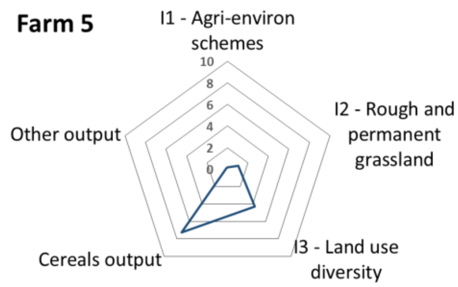

Farm 2
Kernel
Rank


Farm 2
I1 - Agri-environ schemes
I2 - Rough and permanent grassland
I3 - Land use diversity
Cereals output
Other output


Farm 38
Kernel
Rank


Farm 38
I1 - Agri-environ schemes
I2 - Rough and permanent grassland
I3 - Land use diversity
Cereals output
Other output


Farm 5
Kernel
Rank


Farm 5
I1 - Agri-environ schemes
I2 - Rough and permanent grassland
I3 - Land use diversity
Cereals output
Other output

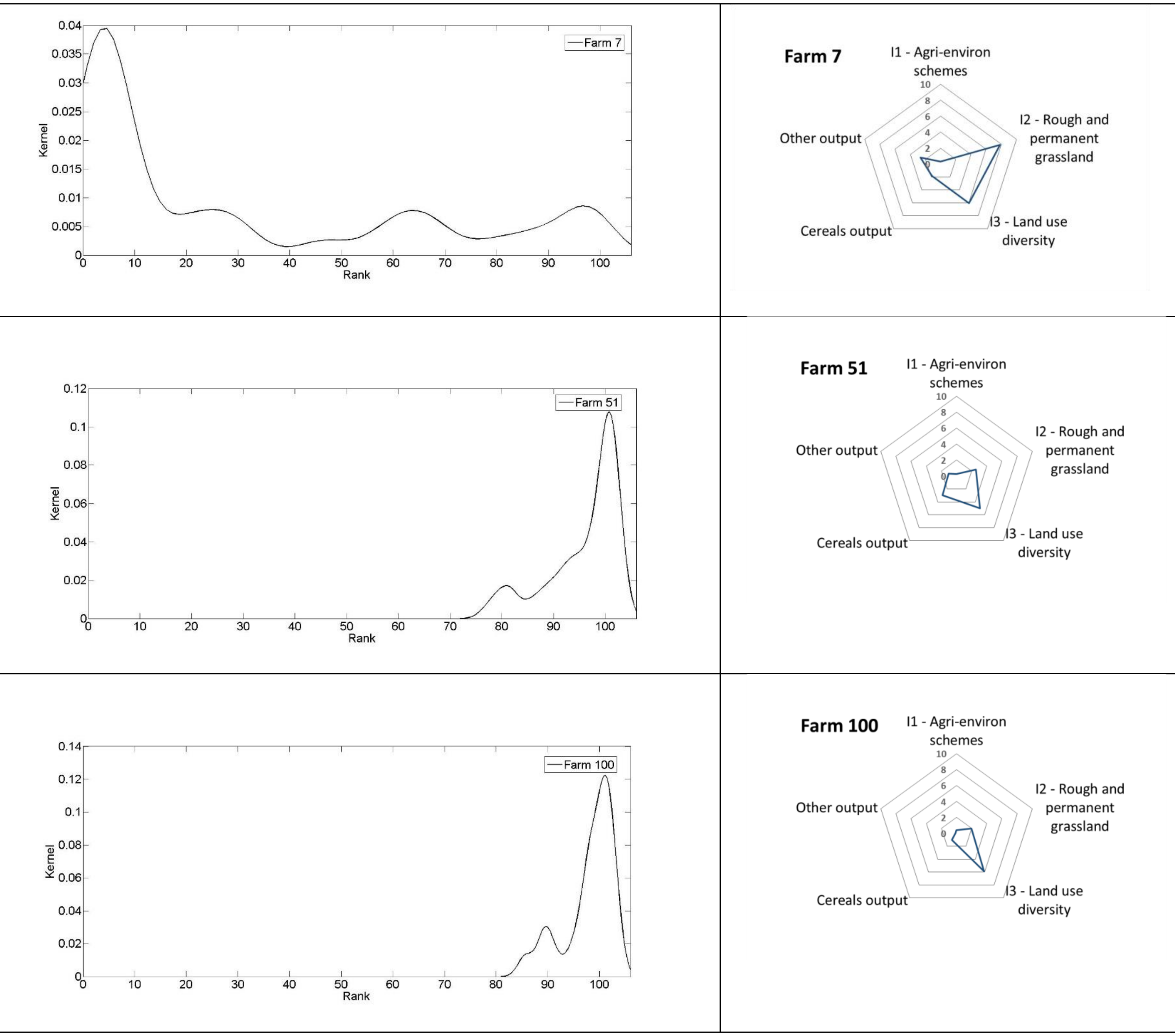


Figure 6. Kernel distributions of individual farm ranking based on efficiency scores, plus radar diagrams showing the scale of a range of provisioning and environmental farm outputs.

The results shown in Figures 5 and 6 raise a question about how robustly farms can be classified according to their SI performance using simple fixed weight composite SI indicators of the type that have appeared in the literature to date. Specifically, how can policy makers, based on the use of such indicators, reward farmers for their environmental outputs, or decide on the nature of the goals to set for farms in different regions to enhance their SI performance?

One way in which the outputs of the current estimation approach could be used for policy analysis would be to classify farms according to their SI distributions. For example, a sample of farms could be divided into quartiles on the basis of SI performance under all environmental outputs : a) the upper SI quartile (USIQ), i.e. farms that are within the first quartile of the distribution under at least one sustainable intensification indicator; b) the second SI quartile (SSIQ), i.e. farms that are not in the first quartile but fall into the second quartile under at least one indicator; c) the third SI quartile (TSIQ), i.e. those that are not in the first two quartiles but are in the third quartile under at least one environmental indicator; and d) the lower SI quartile (LSIQ), i.e. farms that always fall into the fourth quartile irrespective of the environmental indicator used.

Figure 7 demonstrates that, using this approach, high and low levels of sustainable intensification can be found in all landscape types except for south eastern wooded and mixed agricultural landscapes, where all farms in the area are ranked within USIQ (upper quartile) or SSIQ (second quartile) on the basis of our analyses. Most of the TSIQ and LSIQ farms are located in chalk and limestone mixed arable landscapes. It might be argued that these differences in SI performance are heavily determined by the underlying geology and topology that form these landscapes, via constraints on the environmental outputs that can be delivered from the farms within these areas. This further highlights the policy complexity surrounding SI (Wilson, 2014; Barnes and Thomson, 2014) and strongly suggests that incentives to promote increases in SI, inclusive of environmental outputs, need to be context-specific (Armsworth et al., 2012) and feasible within the landscape or catchment where the farm exists. Promoting policies which encourage SI based on a narrowly defined concept, or measurement, of SI, i.e. a ‘one-size-fits-all’ model, are inherently flawed and likely to lead to irrational policy goals and impacts in some areas due to the heterogeneous nature of landscapes. This is as true in England, as in the rest of the world.

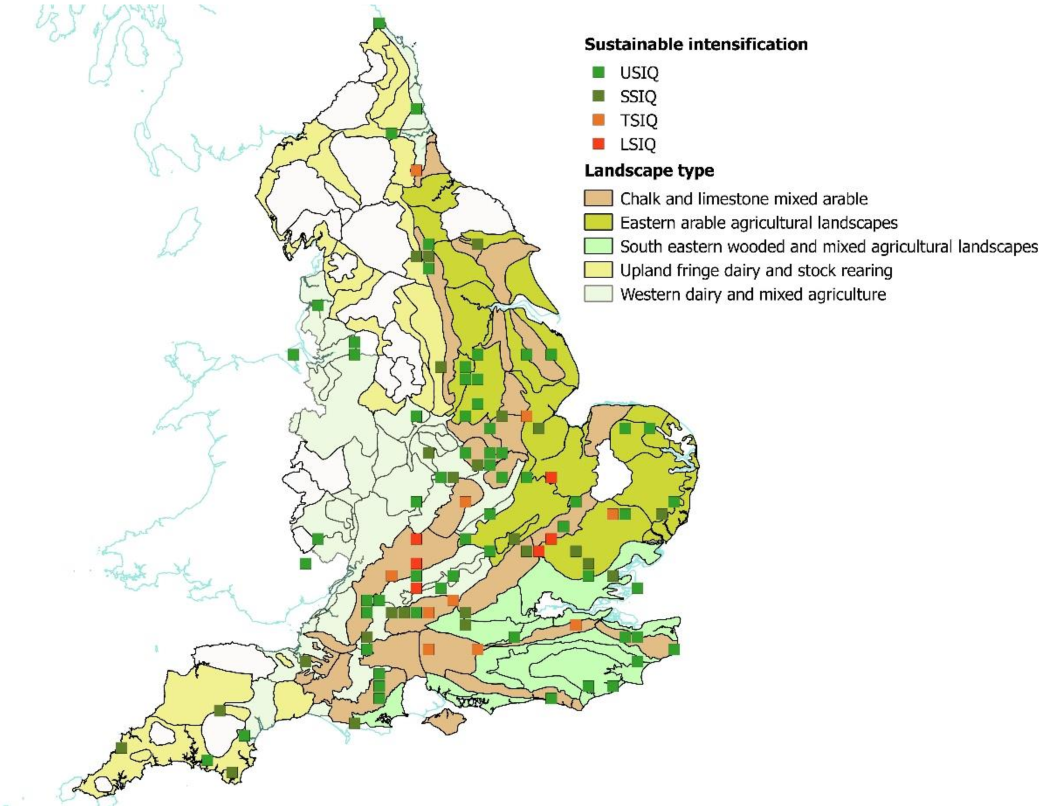


Figure 7. Spatial distribution of farm SI[10] performance by quartiles and landscape type

4 Conclusions

Accounting for the interlinkages between ecological and agricultural systems in economic analysis is crucial to provide useful recommendations to policy makers. However, such relationships are difficult to model, making economic analysis of agro-ecological systems and related issues challenging. Given this complexity, two main issues arguably arise in the policy context. First, what form should metrics of SI take in order to provide robust comparison between farm types in different locations? Second, how can policy makers draw upon these metrics of SI in order to implement evidence-based policies for the benefit of society through improvements in sustainability? Examining the first question, the results of this analysis demonstrate that while the choice of SI metric has clear impacts on the relative SI performance of farms, most farms are seen to be contributing to sustainability through the provision of at least one environmental output. Because the composite SI index generated in this study incorporates multiple types of environmental output without prejudicing any, it is

[10] The location of the farms are only approximate random locations within the county in which the farm is located. Location of the farms has only been constrained to the farm's landscape type.

arguable that this novel, holistic metric of SI, is an improvement on existing metrics of SI performance. The study has also shown that it is important to place any SI metric used within the context of the landscape in which the farm business operates (Koohafan et al., 2012). However, this novel approach to SI construction would surely go some way to allowing policy makers to design policies that are context specific, i.e. targeted towards location-specific outcomes (Armsworth et al., 2012). Complementary approaches that can add value to policy decisions based on this novel composite SI indicator include the development of typology mapping of location-indicator data (Raymond et al., 2009; Andersen et al., 2007). While these approaches do need to be implemented with prior knowledge of feasible outcome possibilities to avoid unintentional consequences, this limitation can usually be overcome by embedding local knowledge within action plans and, moreover, from a bottom-up approach to enhancing positive environmental outcomes from agricultural land (Posthumus and Morris, 2010). The results of the modelling exercise simply reveal a level of complexity (with regard to the type and extent of environmental outputs provision) that policy makers should address in policy design. The statistical approach taken here could itself be developed and used by policy makers and/or their advisors to map regional, or farm system SI, or environmental outputs provision.

Although it is widely acknowledged that measuring SI may be a challenging task, since definitions of sustainability and SI are, in and of themselves, broad and unspecific, the alternative of failing to acknowledge context-specifics in SI estimation severely limits the value of such SI metrics, especially where these have been derived through the arbitrary choice of a single weighting system for environmental outputs within the indicator (EI), rather than registering a range of both environmental indicators and associated weights, as proposed here.

Acknowledgment

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Appendix

A.1 The conditional likelihood function

We assume a normal distribution with mean 0 and covariance matrix $h^{-1}I$ for the likelihood function; X_i is vector of fixed non-stochastic variables, which include inputs and all other outputs; z_i and ε_j (i.e. the error term and the farm inefficiency) are independent of each other for all i and j. The conditional likelihood functions for expressions (9) and (10), with $p()$ referring to the density and $p(|)$ to the conditional density, are[i]:

$$p(y|\beta,h,z) \propto h^{\frac{N}{2}} exp\left[-\frac{h}{2}(y_i - X_i\beta)'(y_i - X_i\beta)\right] \quad (12)$$

A.2 The priors

The likelihood function must be complemented with a prior distribution on the parameters $(\rho, \beta, \psi, h, \mu_z^{-1})$ to conduct Bayesian inference. An independent Normal-Gamma prior is used for the coefficients in the production frontier and the error precision h. We follow the approach used by Fernández et al. (2000) and Koop et al. (1997) regarding the prior for z. Hence, an r-dimensional parameter vector $\phi = (\phi_1, \ldots, \phi_r)$ is added where each of the elements of the parameter vector ϕ measures the effect of the inefficiency explanatory variables k_{ij} on the inefficiency distribution. Given ϕ, z has a probability density function given by

$$p\left(z_i|\mu_z^{-1}(\phi)\right) = \frac{z_i^{\alpha-1}}{\mu^j\Gamma(\alpha)} exp(-{\mu_z}^{-1}(\phi)z_i) \quad (13)$$

where $\Gamma(\cdot)$ indicates the Gamma function and $f_G(z_i|\alpha, {\mu_z}^{-1}(\phi))$ is the Gamma density with parameters α and ${\mu_z}^{-1}(\phi)$, mean $\mu_z(\phi)$, variance ${\mu_z}^2(\phi)$; being $\mu_z^{-1}(\phi) = \prod_{j=1}^{r} \phi_j^{k_{ij}}$ where k_{ij} are dummy variables and $k_{i1} = 1$. An exponential distribution (i.e. $\alpha = 1$) is commonly assumed in the literature (Areal et al., 2012; Fernández et al., 2000; Koop et al., 1997; van den Broeck et al., 1994) which makes the prior for z

$$p\left(z_i|\mu_z^{-1}(\phi)\right) \propto exp(-{\mu_z}^{-1}(\phi)z_i) \quad (14)$$

The priors for each of the elements of the vector ϕ are taken to be independent and follow a Gamma density with hyperparameters $e_j = 1$ and $g_j = -ln(r^*)$ with $r^* = 0.80$ being consistent with farms expected to be close to the frontier under a competitive market (van den Broeck et al., 1994).

A.3 The joint posterior and conditional posteriors

The Bayesian model is defined through the following joint posterior distribution.

$$p(\beta, \psi, h, \mu_z^{-1}, z, |y) \propto p(y|\beta, \psi, h, \mu_z^{-1}(\phi), z)p(\beta)p(\psi)p(h)p\left(z|\mu_z^{-1}(\phi)\right)p(\phi) \quad (15)$$

After extracting the kernel for β, ψ from expression (14) the conditional posterior for β, ψ are normal distributions

$$p(\beta, \psi | h, \mu_z^{-1}(\phi), z, y) \sim N(b, \bar{V}) \tag{16}$$

The conditional posterior for h is a Gamma distribution

$$p(h | \beta, \psi, \mu_z^{-1}(\phi), z, y) \sim G(\bar{s}^{-2}, \bar{v}) \tag{17}$$

The conditional posterior for ϕ follows a Gamma distribution

$$p\left(\phi_j | y, \beta, \psi, h, \mu_z^{-1}(\phi), z\right) = f_G\left(\phi_j | e_j + \sum_{i=1}^{N} w_{ij}, g_j + \sum_{i=1}^{N} w_{ij} z_i \prod_{s \neq j} \phi_s^{w_{is}}\right) \tag{18}$$

The conditional posterior for z_i is

$$p(z_i | \beta, \psi, h, \mu_z^{-1}(\phi), y) \propto exp\left(-\frac{hT}{2}\left(z_i - \bar{X}_i\beta - \bar{ei}_i\psi + \bar{y}_i + \frac{\mu_z^{-1}(\phi)}{Th}\right)^2\right) \tag{19}$$

where $\bar{y}_i = \sum_{t=1}^{T} \frac{y_{it}}{T}$, $\bar{X}_i = \sum_{t=1}^{T} \frac{x_{it}}{T}$, $\bar{ei}_i = \sum_{t=1}^{T} \frac{ei_{it}}{T}$